PhD Thesis Presentation

Studies on 3D-based plant phenotyping by multi-scale data fusion

マルチスケールデータ融合による植物表現型の3次元計測に関する研究

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CONTENT

Introduction

Close-range pipeline



Cross-scale 4 data-fusion

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Introduction



1.1 General background

Accurate and comprehensive data collection helps effective decision-making in agriculture







Traditional approach hard to meet such demand

High-throughput phenotyping technologies

[1] https://www.forbesindia.com/fbimages/900x600/proportional/jpeg/blog/wp-content/uploads/2023/01/Agriculture-is-a-potential-solution-to-meet-food-and-climategoals.jpg



1.2 Limitation of existing methods



Aerial approach (distance to object > 5m)



Survey entire farmland efficiently





Low quality of organ structure



Close-range approach (distance to object < 2m)

Obtain better organ structure



Low efficiency for surveying entire farmland



1.3 Research objective





Can we obtain high-quality organ structure of entire farmland efficiently by fusing both approaches?



Close-range 02 3D pipeline



2.1 Background

Traditional close-range 3D phenotyping pipeline





2.2 Challenge

Traditional method cannot obtain complete organ structure







2.3 Solution

Implement an automatic data collection and 3D reconstruction pipeline



Automatic image collection

Dual rotation reconstruction pipeline



2.3 Results - obtained high-quality 3D model





Obtained 3D model



Data pool of 3D highquality broccoli heads

2.3 Results - 3D data processing

Calculate 3D-based morphological traits



Visualization

	Traits	Unit
1D	Crown/head height (m)	m
	Center point (x, y)	m
	Centroid point (x, y)	m
	Roundness	-
2D	Minimum area rectangle (width, length)	m
	Ellipse axis length (long, short)	m
	Ellipse orientation	degree
	2D convex area	cm ²
	Projected area	cm ²
3D	3D Convex volume	cm ³
	3D Concave volume	cm ³



As model attributes

Final output traits list



2.3 Results - traits accuracy validation

Compare the shortest and longest length (hard to do manual measurements for 2D and 3D traits)

shortest head length

longest head length





2.4 Conclusion

Obtained the high-quality and complete 3D models

Calculated the 3D-based traits and validated accuracies

Built a data pool for high-quality broccoli head 3D models



Aerial 3D 03 pipeline



3.1 Background

Traditional aerial phenotyping pipeline







Collect raw UAV images



Digital ortho-mosaic (DOM)

Digital surface model (DSM)





Organ segmentation

Morphological traits calculation



3.2 Challenges

1. Need to analysis huge amount of image data (difficult to process in time)





3.2 Challenges

2. Hard to achieve the quality for organ-level analysis from aerial reconstruction





3D canopy model (PCD) 2D field map (DOM)

3.2 Challenges





3. Complex natural environment conditions makes segmentation tasks difficult (deep learning needs large number of training data)



Huge differences between time, sunlight, soil condition, growing stage, cultivars



3.3 Solutions for analyzing huge amount of image data =

Temporal data fusion

narrow the processing regions by using prior knowledge of agriculture





Broccoli head position is almost the same as its seedling position

Narrow the processing area around the seedling area

(100 x 100) pixels x 3000 count = 30 billion pixels per flight ~ one raw image per crop 5742 x 3648 ~ 20 billon pixels



3.3 Solutions for not enough aerial quality

Spatial data fusion

combine raw images (pixel coordinates) with field maps (geo coordinates)



(2341,1492)

Pixel coordinates

Better quality Lacks spatial context





A handy tool for dealing with region of interest (ROI) on the image reconstruct mainly in agriculture applications

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11 0

Updated last month

ATA MIT

Pvthor



3.3 Solutions for lacking training data

Deep learning data fusion low labor cost for training data annotation

pre-trained models



(a) Transfer learning





(b) Data augmentation

(c) Active learning



3.4 Results – temporal & spatial data fusion



Seeding detection by pre-trained Yolo v5

Temporal (time-series) data fusion during growing stages

Head Segmentation results



3.4 Results - traits calculation

For each broccoli head



Minimum area rectangle max/min side-length

Equivalent diameter

broccoli center points

Eccentricity, circularity

Major axis length Minor axis length

Area, perimeter

Convex area



3.4 Results - traits accuracy validation

2020 head diameter (mm) 2021 head diameter (mm) 250 300 (a) (c) 200 225 measured 150 **Y**: 150 Manual field measured Manual 100 May 12, R²=0.7187 75 May 15, R²=0.7322 50 May 22, R²=0.7416 May 19, R²=0.5996 May 26, R²=0.6651 May 20, R²=0.5771 May 28, R²=0.6054 May 26, R²=0.6405 0+0 0+0 150 75 225 50 100 200 250 150 300

Has acceptable correlation with manual measured head size

X: Aerial measured



3.5 Conclusion

- Developed temporal data fusion method with prior knowledge of agriculture to dramatically save the computation cost
- Developed spatial data fusion to improve the organ-level image quality
- Developed deep learning data fusion to decrease the workload of training data annotation for head segmentation
- Improved 2D-based traits of broccoli head and validated by manual measurement



Cross-scale 04 data fusion



4.1 Background

Part 2: close-range 3D pipeline





Part 3: aerial 3D pipeline



Part 4: cross-scale data fusion







Head shapes & positions in entire farmland High quality head models of entire farmland



4.3 Solutions for cross-scale data fusion





4.4 Results - cross-scale data fusion



Aerial segmentation results

Aerial field 3D models

Data fusion results



4.4 Results - cross-scale data fusion





4.5 Conclusion

Calibrated the shape errors caused by occlusion

Selected the calibration model automatically by Auto-ML

Developed data fusion workflow to place the best match from close-range data pool back to aerial field model



Conclusion



5.1 Highlights

Chapter 2

Built a close-range high-quality data pool with 3D-based morphological traits for 189 broccoli heads

Chapter 3

Decreased the aerial image processing workload and improved the organ-level accuracy by temporal and spatial data fusion

Chapter 4

Developed aerial & close-range data fusion to place highquality 3D models back to field.

5.2 Future work



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Explore the deep learning 3D reconstruction approach, like NERF^[1] (faster and better quality)

Improve the data fusion approach by procedural modeling for complex plant structures



Achievements

Journals

- Wang, H., Duan, Y., Shi, Y., Kato, Y., Ninomiya, S., Guo, W., 2021. EasyIDP: A python package for intermediate data processing in UAV-based plant phenotyping. *Remote Sensing* 13, 2622. <u>https://doi.org/10.3390/rs13132622</u> (Published)
- Wang, H., Tang, L., Nishida, E., Fukano, Y., Kato, Y., Guo, W., Drone-based harvest data prediction can reduce on-farm food loss and improve farmer income *Plant Phenomics*. (Under review)
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- Wang, H., Tang, L., Nishida, E., Fukano, Y., Kato, Y., Guo, W. July 20-22, 2021. Cost-efficient broccoli head phenotyping using aerial imagery and SfM-based weakly supervised learning, The 8th International Horticulture Research Conference, Nanjing, Jiangsu, China. (poster)
- Wang, H., Kato, Y., Guo, W., June 3-4, 2021. EasyIDP: A python package for intermediate data processing in UAV based plant phenotyping, 超分野植物科学研究会の第 1回研究集会 2021, Zoom online, Tokyo, Japan. (poster)
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